Operational Risk: Emerging Markets, Sectors and Measurement

Mitra, S., Karathanasopoulos, A., Sermpinis, G., Dunis, C. and Hood, J.

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by

Sovan Mitra

Glasgow Caledonian University,

Cowcaddens Road, Glasgow, G4 0BA.

Tel.: 0141 331 3000

email: sovan.mitra@gcu.ac.uk

Abstract

The role of decision support systems in mitigating operational risks in firms is well established. However, there is a lack of investment in decision support systems in emerging markets, even though inadequate operational risk management is a key cause of discouraging external investment. This has also been exacerbated by insufficient understanding of operational risk in emerging markets, which can be attributed to past operational risk measurement techniques, limited studies on emerging markets and inadequate data.

In this paper, using current operational risk techniques, the operational risk of developed and emerging market firms is measured for 100 different companies, for 4 different industry sectors and 5 different countries. Firstly, it is found that operational risk is consistently higher in emerging market firms than in the developed markets. Secondly, it is found that operational risk is not only dependent upon the industry sector but also that market development is the more dominant factor. Thirdly, it is found that the market development and the sector influence the shape of the operational risk distribution, in particular tail and skewness risk. Furthermore, an operational risk measurement method is provided that is applicable to emerging markets. Our results are consistent with under investment in decision support systems in emerging markets and imply operational risk management can be improved by increased investment.

Key words: operational risk, emerging markets, sector, risk management, investment.

1 Introduction

Operational risk, the risk arising from operational activities, has been gaining increasing attention as a source of risk within firms (Beroggi and Waliace, 2000). The role of decision support systems in reducing costs and operational risks is well established within literature; there has been much research documenting that decision support systems improve operational performance (see for instance (Repede and Bernardo, 1994), (Clark and Chapman, 1987), (Beroggi and Wallace, 1994) and (Chan et al., 2000)).

Despite this, little analysis has been done to quantify the degree of operational risk in firms, yet a key role of decision support systems is reducing operational risk. Consequently, the importance of decision support systems in relation to managing operational risk is not fully understood. For instance, is operational risk sufficiently low enough (compared to other firms) or is additional decision support systems investment required? Did past decision support systems investments improve (or worsen) operational risk and if so by how much?

The ability to answer such questions and benchmark one's operational risk performance is especially important in emerging markets, where it is recognised that companies tend to be exposed to greater operational risk e.g. system errors, fraud etc. (see for instance (Ray and Das, 2010) and (Smimou, 2013) who cites fraud as an important factor in emerging markets). Emerging markets have attracted significant interest in industry and research (e.g. (Zmeskal, 2005), (Kallio et al., 2012), (Vidal-Garcia and Vidal, 2014), (Dong et al., 2013)). Despite that operational risk is an important factor in emerging markets, there is a lack of investment in decision support systems in emerging markets when their firms are compared to their peers in developed markets (see (Berardi et al., 2004), (Meng and Lee, 2007)). This is even more puzzling given that there exist incentives to invest in decision support systems; foreign investors tend to avoid emerging markets solely due to operational risk issues (see (Khanna et al., 2005), (Khanna and Palepu, 2006)).

The fact that incentives exist to implement decision support systems in emerging market firms but do not invest in them suggest that they do not fully comprehend their level of operational risk exposure. This has been due to a number of interacting reasons. Firstly, most research relating to operational risk has not focussed on emerging markets. Hence emerging market firms have less understanding on their operational risk, which in turn impacts decision support systems expenditure. Secondly, emerging markets typically present significant data acquisition challenges and so applying any quantitative methodology becomes impractical. Hence, the understanding and analysis of operational risk in emerging markets has been limited.

Thirdly, there has been little development in techniques to quantify operational risk. The current methods of quantifying the impact of decision support systems have not focussed upon operational risk or any risk measurement, rather they have focussed around event studies (such as in (Meng and Lee, 2007) and (Chai et al., 2011)) and cost-benefit analyses (for example (Gayialis and Tatsiopoulos, 2004), (Santhanam and Kyparisis, 1996) and (Ozdamar et al., 1998)). The cost-benefit analyses typically focus on cost reductions and efficiency savings; the event study method examines the benefit in share returns from introducing systems. Both methods do not quantify risk but also they focus on the operational gains from a single system, rather than examining the operational risk of the overall company, hence their analysis is limited in scope.

In the past decade, operational risk literature has significantly developed; various methods and techniques have been developed which now enable us to analyse operational risk more effectively. For instance, models and data are now being utilised to quantify the operational risk of firms ((Chorafas, 2004), (Loader, 2002)). This now enables us to compare the operational risk between firms, markets and sectors and so enable us to determine whether firms are adequately managing their operational risk (e.g. through sufficient decision support systems investment). However, the literature on decision support systems and operational risk in emerging markets has been practically non-existent. Furthermore, many operational risk measurement techniques have demanding data requirements that prohibit their application to emerging markets (since such markets have low data availability).

In this paper the operational risk in emerging and developed markets is measured and compared for 100 different firms, over 4 different industry sectors and in 5 different countries. Our operational risk measurement method utilises publicly available financial data that is available in emerging and developed markets; in particular stock price data from 2007-12 is used and other empirical financial data such as balance sheets. Hence our method does not prohibit analysis of emerging markets.

This paper makes a number of contributions. Firstly, a method of measuring operational risk is provided that is applicable to developed and emerging markets; it is not prohibited from investigating emerging markets by circumventing significant data demands. Secondly, it is shown that operational risks are dependent on the level of market development (specifically emerging or developed), suggesting that emerging market firms are significantly underfunded in decision support systems. Thirdly, it is found that there is a dependency on operational risk to industry sector, which is expected since differing industries have differing exposure to operational risk . Fourthly, it is found that the level of market development is more important than the industry sector in determining operational risk. Finally, market and sector factors affect the shape of the operational risk distribution, in particular skewness and tail risk. Such results are consistent with insufficient investment in decision support systems in emerging markets.

The rest of the paper is organised as follows: in the next section operational risk is introduced, defining it, the motivation for study and providing a literature review of related research. The next section explains the method for measuring operational risk, its implementation and calibration. The proceeding section explains our method, data, presents our results and analysis. The paper finally ends with a conclusion.

2 Introduction to Operational Risk and Motivation of Study

Risk management is one of the key functions of any business (see for instance (Mitra et al., 2013), (Fertis et al., 2012), (Ansaripoor et al., 2014), (Gaivoronski et al., 2012),(Singh et al., 2013)), although the 2008 financial crisis demonstrated the continued existence of weak risk management practices (Voinea and Anton, 2009). Operational risk is the risk arising from the operational activities in conducting business, rather than the business's 'financial' risk; in (Hahn and Kuhn, 2012) defines operational risk as the result from the uncertainty of future events in the ordinary course of business. Examples of operational risk include I.T. failure (physical or software), damage to physical assets (e.g. through natural disasters), administration errors (e.g. incorrect data entry), fraud and other operational activities. Operational risk is therefore encountered by all types of businesses, regardless of industry sector.

Operational risk has increased over the years as operations have begun to play an increasingly prominent role in businesses. The primary reasons for this are that firstly companies use highly sophisticated technologies to manage operations nowadays (Chowdhury, 2003). This typically increase the risk in operations and so the likelihood of unpredictable losses. Secondly, businesses have increased their degree of reliance upon operational activities over time, hence they become increasingly more vulnerable to operational risks. For instance, (Westland, 2002) and (Ngai and Wat, 2005) discuss the operational risks associated with e-commerce and the impact on businesses.

The literature on decision support systems playing crucial roles in reducing operational risk has been well established. For example, in (Ngai and Wat, 2005) the importance of operational risk is highlighted in e-commerce and its impact on businesses. In

(Hong and Lee, 2013) the operational risk confronting procurement processes is investigated and decision support systems are proposed to model various operational risks that exist. In (Garcıa-Dastugue and Lambert, 2003) discuss the use of internet specific decision support systems in reducing operational risk facing companies in supply chain related risks. In (Kim et al., 2012) yield management decision support systems reduce operational losses but also improve workforce utilisation.

Despite the acknowledged importance of decision support systems in improving operational risk management in firms, it has been recognised in various studies that emerging market firms typically do not have the same level of decision support systems as in developed markets. For instance (Berardi et al., 2004) point out that emerging market firms are unable to take advantage of decision support systems due to emerging markets firms having inadequate systems. In (Meng and Lee, 2007) it is discussed that the gap between developed and developing countries is widening due to the slow adoption of IT systems.

A potential explanation for the lack of decision support systems investment in emerging markets could be attributed to a lack of investment demand in such firms, however, emerging market firms typically attract high investment demand. In fact, the emerging markets have attracted significant investment demand from investors in developed markets. This can be explained by a number of factors. Firstly, they offer potentially relatively higher returns than their domestic counterparts. Secondly, investment in emerging markets enables one to diversify his portfolio. Thirdly, stringent capital controls have become increasingly relaxed, which has encouraged foreign investment in emerging markets.

The lack of investment in decision support systems is even more puzzling given that a key cause for discouraging foreign investors in emerging markets arises from poor operational risk management. For instance in (Khanna et al., 2005) the operational risk arising from a lack of regulatory systems in emerging market firms lead to foreigners avoiding investment in such firms; in fact American firms believe they operationally perform better in their home country than in emerging markets. In (Khanna and Palepu, 2006) emphasise the importance of operational execution and governance in building world class companies in emerging markets, yet there are varying degrees of emphasis placed on governance (Khanna and Palepu, 2006).

Despite that incentives exist to invest in decision support systems, the shortfall in investment therefore suggests there is a lack of understanding operational risk within emerging market firms. This can be attributed to a number of key reasons: data issues, lack of operational risk techniques and a deficiency of operational risk or decision support systems studies in emerging markets. Firstly, with respect to insufficient operational risk or decision support systems studies in emerging markets, the majority of literature on operational risk or decision support systems has been primarily focussed on developed markets (Chowdhury, 2003). For example in (Blass et al., 1998) they comment that most corporate governance research has focussed on developed markets, rather than emerging markets, yet such governance is crucial to operational risk management.

Secondly, operational risk analysis in emerging markets is scarce because there is typically insufficient data for the studies (see for instance (Chowdhury, 2003), (Chai et al., 2011)). The required data for emerging market firms is frequently unavailable, either publicly or from proprietary databases, as the relevant data is not recorded. Moreover, current operational risk methods have been known to be highly restrictive in application due to their non-trivial data requirements. Consequently, applying any methodology to emerging markets is non-trivial.

Thirdly, there has been inadequate development of operational risk techniques in the past, hence the examination of the impact of decision support systems upon companies has been practically non-existent. The majority of studies examining the impact of decision support systems on firms in emerging markets have taken the form of event study methodologies; see for instance (Chai et al., 2011), (Bose and Pal, 2012). Event studies examine the impact on share prices due to the introduction of some system, for instance (Meng and Lee, 2007) analyse the impact on Chinese share prices following the introduction of a new IT system. However, event studies require choosing an expected returns model and the choice can significantly vary between studies, yet results can be significantly impacted by model choice. Other decision support systems studies have examined their impact in terms of costs and benefits yet risk is not analysed. Although some decision support systems studies perform operational risk analysis it is highly non-quantitative (see for instance (Van Wyk et al., 2004)) and so has limited analytical use.

In all the previously mentioned methods, given that operational risk in firms is not typically analysed, our comprehension of decision support systems in managing operational risk is impacted. The understanding is limited and the non-quantitative analysis of operational risk that is undertaken has minimal insight. Furthermore, all of these methods are typically focussed upon analysing the operational benefits arising from a single source, system or entity. Therefore, the entire operational issues or operational risk of the entire firm are not examined, hence the analyses are typically limited in scope.

In the past decade the literature in operational risk has significantly grown (see for instance (Chorafas, 2004) and (Loader, 2002)). Using such literature and techniques it is now possible to measure operational risk in firms more effectively; operational risk of firms can be quantified in different sectors and markets. However, there is still insubstantial literature with respect to operational risk in emerging markets; this has also been exacerbated by a lack of data in such markets. Moreover, many operational risk measurement techniques have significant data requirements (to be discussed in the proceeding section) which prohibit their application to emerging markets. This leads us to devising an operational risk measure that allows us to measure operational risk in emerging markets, based on the Single Index Model (Zvi et al., 1999), and to address the following research questions:

-To compare the operational risk of emerging markets to developed markets and to determine to what extent emerging market firms are (more or less) riskier than developed markets?

-To compare the operational risk across different industry sectors to determine to what extent operational risk varies between sectors?

-To determine how the shape of the operational risk distribution varies with market development and industry sector, in particular with respect to skewness and tail risk?

3 Operational Risk Measurement Methodology

In this section the operational risk measurement methodology is introduced, explaining the operational risk measure, its calibration and implementation.

3.1 Operational Risk Measurement

To measure operational risk in emerging markets requires a measure that does not impose stringent data requirements. This is because emerging markets are typified by scarcity of any data in general; given that operational risk data is frequently unavailable in developed markets, therefore emerging markets will not provide substantial operational risk data (see for instance (Chowdhury, 2003), (Chai et al., 2011)).

The specification of an operational risk measure with undemanding data needs is a non-trivial requirement, given that many operational risk measures impose significant data requirements. For instance, (Cummins et al., 2006) requires a proprietary database to measure operational risk; such databases are difficult to obtain for confidentiality reasons but also are unlikely to exist for emerging market firms. In (Allen and Bali, 2007) operational risk is examined without a proprietary database but still requires large amounts of empirical data that may not exist in emerging markets.

Other operational risk measures exist that have fewer data requirements (such as the Basic Indicator Approach and Standardised Approach) but they are inappropriate for this study for 2 key reasons. Firstly, such measures are typically focus towards particular industry sectors and so would not be applicable to a range of sectors, as required in our paper. Secondly, such measures can be theoretically inconsistent, for instance they explicitly imply that higher profitability must lead to higher operational risk. Yet higher profitability can directly arise from lowering operational risk.

From risk measurement theory one can quantify risk by applying some appropriate statistical measure to the return distribution (Artzner et al., 1997); examples are quantiles (or Value at Risk) and standard deviation (Szego, 2005). To measure operational risk therefore requires applying some statistical measure to the return distribution attributed to operational risk only. A popular definition of operational risk assumes that total risk of company A , R(A), is given by

$$R(A)=R_M(A)+R_C(A)+R_{OR}(A), \tag{1}$$

where $R_M(A)$,$R_C(A)$, $R_{OR}(A)$ are the market, credit and operational risk, respectively, of company A. Therefore operational risk is measured as the residual risk remaining once market and credit risk are removed (Loader, 2002).

To obtain the return distribution due to operational risk (from which one can obtain a measure of operational risk using a statistical measure), one can quantify the returns from operational risk using the Single Index Model (SIM) and equation (1). The SIM is a well established financial model for stock prices in academic literature and it is also used in industry. The SIM has been widely studied in a number of papers (see for instance (Kwan, 1984), (Chen and Brown, 1983), (Ahmed, 2007), (Bilbao et al., 2007)) and an accepted model for stock returns. Furthermore, the SIM is applicable to any sector and it is able to account for stock returns whilst also being consistent with the financial theory of risk; such properties are important to risk measurement in our paper.

Under SIM the return of asset i at time t, $r_i(t)$, is given by

$$r_i(t)=\alpha_i+\beta_i[r_M(t)-r_f(t)]+r_f(t)+e_i(t) \tag{2}$$

and $$E[r_i(t)-r_f(t)]=\alpha_i+\beta_i E[r_M(t)-r_f(t)], \tag{3}$$

where:

- $r_M(t)$ denotes the return of the market or a stock market index;

- $r_f(t)$ denotes the riskless rate;
- α_i, β_i are the alpha and beta of asset i, respectively;
- $e_i(t)$ is the residual of asset i.

In the SIM model the market risk returns are given by

$$\beta_i E[r_M(t)-r_f(t)], \tag{4}$$

hence the total stock return with returns due to market risk removed is given by

$$r_i(t)-\beta_i E[r_M(t)-r_f(t)]. \tag{5}$$

One also notes in passing that this equation is also equal to

$$\alpha_i + r_f(t) + e_i(t), \tag{6}$$

by applying equation (2).

Using equation (1), one can therefore obtain stock returns due to operational risk if one can remove returns due to credit risk from equation (5). In other words, returns due to operational risk factors for asset i, $\varphi_i(t)$, is given by

$$\varphi_i(t)=r_i(t)-\beta_i E[r_M(t)-r_f(t)]-y_i(t), \qquad (7)$$

or alternatively,

$$\varphi_i(t)=\alpha_i+r_f(t)+e_i(t)-y_i(t), \qquad (8)$$

where $y_i(t)$ is the returns from credit risk factors. Once one can calculate $\varphi_i(t)$ one can then obtain a distribution of operational risk returns of $\varphi_i(t)$ and therefore apply some risk measure to calculate the operational risk.

Our measurement of operational risk has a number of advantages. Firstly, compared to many operational risk measures, it does not have demanding data requirements. The method requires data that is easily obtainable, such as stock prices and other market data (e.g. interest rates). Hence our method can be applied to developed as well as emerging markets, which is the main purpose of this study. If one were to use risk measures using operational loss databases then one could only study a limited number of markets and sectors.

Secondly, our method can be applied to a range of sectors. The SIM model (and calculation of $y_i(t)$ to be discussed in the proceeding section) can be applied to any sector. As mentioned previously, some operational risk measures are not applicable to all industry sectors, however our method allows measurement and comparison of operational risk across different sectors. Thirdly, the measure does not pose significant calibration and implementation problems. The SIM model is known for its parsimony of calibration and implementation (Zvi et al., 1999); the credit returns $y_i(t)$ calculation will be discussed in the next section.

3.2 Implementation and Estimation of Operational Risk

To measure operational risk requires obtaining the distribution $\varphi_i(t)$ and applying some statistical measure to it. To determine $\varphi_i(t)$ requires estimating market risk returns, which requires estimation of β_i and r_M. The r_M is observable from any stock market index return data, which is typically available from public sources (in developed or emerging markets), hence does not require estimation. Similarly, r_f data is also publicly available in any market and so does not require estimation. The β_i is estimated by standard linear regression; one regresses

$$Y=mX+C+\epsilon_i(t) \qquad (9)$$

where

- $Y=r_i(t) - r_f(t)$;
- $m=\beta_i$;
- $X=r_M(t) - r_f(t)$;
- C is a constant;
- $\epsilon_i(t)$ is the error term.

Therefore β_i is estimated from the gradient of the regression equation. There exist numerous built-in functions for standard linear regression for different packages; Matlab was used for our regression.

A method of estimating $y_i(t)$ was required and the SIM theory provides no method on measuring credit risk returns. Additionally, our measurement method must enable measurement in a range of sectors and emerging markets. An obvious measure of credit risk returns would be corporate bond yields for each stock, however such data is not always readily available, especially in emerging markets. Other possible models to estimate credit risk returns include analytical models such as the Leland and Toft model (Leland and Toft, 1996) or Denzler et al. (Denzler et al., 2006), however these make unsuitable assumptions for our study (e.g. credit risk is independent of the sector) and more stringent data requirements than using corporate bonds. Reduced form models (e.g. Jarrow-Turnbull model (Jarrow and Turnbull, 1995)) also have demanding data requirements but also the results are significantly sensitive to calibration.

An appropriate method for calculating $y_i(t)$ is Merton's structural model of default (Merton, 1974); this method has been applied in academic research and industry. The principal idea behind Merton's model is that the credit risk event of default behaves like a financial option. One assumes that a company has an amount of debt due at a future time T and that the company defaults if the value of its assets is less than the required debt repayment at time T.

The shareholder's equity value is given in Merton's model by

$$E(T)=[A(T)-D(T)]^{+},$$

where

- T is the expiry date of the debt;
- E(T) is the market value of company's total equity at time T;
- A(T) is the total value of company assets at time T;
- D(T) is the total value of company debt at time T.

As credit default behaves like a European call option it is possible to apply the Black-Scholes equation (Black and Scholes, 1973) and obtain the credit risk return associated with a stock. In (Hull et al., 2004) the credit risk return $y_i(t)$ is given by

$$y_i(t)=r_f(t)-(ln[N(d_2)+(N(-d_1)/L)])/(T-t) \quad (10)$$

where

$$d_1=-lnL/(\sigma_A\sqrt{(T-t)})+0.5\sigma_A\sqrt{(T-t)}, \quad (11)$$

$$d_2=d_1-\sigma_A\sqrt{(T-t)}, \quad (12)$$

$$L=D(t)e^{-r(T-t)}/A(t)=D^*(t)/A(t), \quad (13)$$

and

- T is the credit risk return period for y_i at time t (and the expiry date of the debt);
- σ_A is the volatility of company i asset value;

- A(t) is the total value of company i assets at time t;
- D(t) is the total value of company i debt at time t;
- N(.) is the cumulative distribution function for the standard Normal distribution.

To estimate $y_i(t)$ requires estimation of L, which in turn requires D(t). The total liabilities for D(t) are obtained using the same methodology in (Hull et al., 2004); one uses company financial statements and these are typically available for all publicly traded companies in emerging markets.

To determine $y_i(t)$ one needs to calculate A(t) and σ_A. To estimate the variables A(t) and σ_A one uses a set of equations from Merton's credit risk model:

$$E(t)\sigma_E = N(d_1)A(t)\sigma_A, \tag{14}$$

$$\sigma_E = \sigma_A N(d_1)/(N(d_1) - LN(d_2)), \tag{15}$$

where

- E(t) is the market value of the company's total equity at time t;
- σ_E is the stock price volatility.

The stock volatility σ_E can be estimated by standard econometric methods and E(t) can be observed at time t as it is the stock price multiplied by the number of shares issued in the company.

4 Method

In this paper operational risk returns $\varphi_i(t)$ are calculated using the methodology discussed in section 3 and equation (7). One then calculates risk measures on the distributions obtained for $\varphi_i(t)$ to quantify the operational risk, specifically Value at Risk (VaR) and standard deviation. The skewness is also calculated; skewness has been used in finance to account for understating risks (known as skewness risk). Hence such a variable may explain underestimation of operational risk in emerging markets. Other metrics of interest on the operational risk return distribution were also calculated, such as the mean.

The $\varphi_i(t)$ is calculated using data over 5 years, for 100 stocks, in 4 different industry sectors (utilities, basic materials (mining and raw materials), financial and the technology sector). The stocks were taken over 5 different markets: 3 emerging markets (China, India and South Korea) and 2 developed markets (USA and UK). The $\varphi_i(t)$

is calculated using monthly stock price returns, monthly interest rate data for r_f and monthly market index returns for r_M . As in (Allen and Bali, 2007), a monthly time period was chosen because an annual time frame would not necessarily capture the impact of operational events on stock prices. A weekly time frame was not chosen as this would be too short; weekly returns can be distorted by non-operational factors e.g. market sentiment.

The credit risk return factors $y_i(t)$ were estimated using the method explained in section 3. To determine σ_E, which is required for $y_i(t)$, the method from (Buchbinder and Chistilin, 2007) is applied which involved taking the standard deviation of daily stock returns during each month. The volatility can be scaled to any time scale using the square root of time rule (see (Hull, 2000) for more information).

As the riskless interest rate data can significantly differ between emerging and developed markets, the monthly operational risk returns were calculated with the riskless rate subtracted from them. This was to ensure that particular markets were not gaining high operational risk returns due to higher riskless rates in their respective country. This gives a fairer comparison of operational risk across different markets.

To determine the variables A(t) and σ_A a computational optimisation method to solve the 2 equations was followed, in accordance with (Hull, 2000). To improve the accuracy of estimating A(t) and σ_A, the optimising equation (15) is replaced with optimising the following equation (taken from Merton's model):

$$E(t)=A(t)N(d_1)-D^*(t)N(d_2). \tag{16}$$

This equation is easier for the computer program to optimise and so leads to improved computational results, whilst still providing the required variables. The computational optimisation of equations (14) and (16) was implemented in Matlab, using the fsolve function and option pricing functions in the Matlab financial toolbox.

To verify the validity of the Merton model (although we note that this is already a well-established model and has been verified in industry and in academic research) we examined the credit spread results given by the model. In table 7 (Appendix) the empirical results of using the Merton model to calculate the credit risk returns are given, using the same data used in this paper. The mean risk free rates (Central Bank interest rates) are also given in the Appendix in table 8 for the same time period that the stock data is collected. One can therefore see from the Appendix that the mean credit risk spreads are therefore consistent with expectations, that is low credit risk spreads. We expect a low credit spread because the stock companies in our data are high market capital companies with low credit risk, hence a low credit spread is expected.

5 Data

The stocks were taken over 5 different markets: 3 emerging markets (China, India and South Korea) and 2 developed markets (USA and UK). These markets were chosen to compare the operational risk performance of stocks in developed and emerging markets. In particular China was chosen due to its importance as an emerging market and India was also chosen as it has been cited in literature as having significant operational issues in business. South Korea was chosen as it is considered an emerging market but also is considered a market in an intermediate state between emerging and developed markets, hence it would provide an interesting market for operational risk analysis. The USA and UK markets were chosen as these are generally regarded as good examples of developed markets.

The stocks were taken from the following stock exchanges: Korea Stock Exchange (for Korea), Shanghai Stock Exchange (for China), National Stock Exchange of India (for India), London Stock Exchange (for UK) and New York Stock Exchange (for USA). These exchanges were chosen (rather than alternative exchanges) as they are the largest exchanges in their countries with the highest share trading volume, thereby reducing pricing irregularities due to liquidity effects. For example, the National Stock Exchange of India and the Bombay Stock Exchange are approximately the same size but the National Stock Exchange has a higher share trading volume. To obtain the stock market index returns r_M for each country, the indexes were chosen that were most representative of the exchange. The following stock indexes were used: KOSPI (Korea Composite Stock Price Index for Korea), SSE Composite Index (for China), S&P CNX Nifty (for India), FTSE-100 Index (for UK) and the NYSE US 100 Index (for USA).

The empirical market data (e.g. stock prices, interest data, financial statements) was taken from the past 5 years time sample 2007-12. A 5 year time period was chosen to provide sufficient data points to obtain a distribution on operational risk returns, which enabled operational risk measurement. A 5 year time period was also chosen to ensure operational risk returns were taken over an entire cycle of stock market returns, rather than during a boom or recession period only, which could bias operational risk returns. Furthermore, a 5 year time period enabled one to obtain all stock price data in emerging markets; longer time periods would not allow this.

The sectors were chosen to investigate the impact of different fundamental operational characteristics upon operational risks and share performance. The stocks were chosen to be representative of the desired industry sector but also on the basis of high market capital. This meant that the stocks were most likely to be actively traded, therefore prices would not be distorted by liquidity effects. Also, any new market or company information would be reflected into the stock prices within a short time period, which is important for operational risk measurement. Such properties are especially important in emerging markets where information is less easily disseminated and stock prices can be significantly affected by inactive trading compared to developed markets.

It is worth noting that sector indices were not used in our experiments instead of stocks because sector indices technically are not traded, so there is technically no market capital associated with them and this is required for our credit risk return estimation. Additionally, some markets (particularly emerging markets) do not have suitable indices that enable equivalent comparisons over different countries e.g. a technology sector index may exist in 1 country but in another country only an internet sector index may exist. Furthermore, the weighting and selection criteria for each stock in an index varies with each index, thereby distorting the comparison of sector indices between countries.

To calculate $y_i(t)$, data on total liabilities and market capital is required and these are available from company annual reports which are published publicly (including for emerging markets). Also, the riskless interest rate r_f data is publicly available and provided by central banks for each country.

6 Results and Analysis

In this section the results are presented, followed by a discussion and analysis of results. All figures are in terms of percentage stock returns and S.D. denotes standard deviation.

6.1 Results

6.1.1 Operational Risk and Operational Risk Returns by Market

Table 1: Operational Risk and Operational Risk Returns by Market

Country	USA	UK	S.Korea	India	China
Mean	0.15	0.29	0.17	-0.51	0.29
S.D.	8.83	9.39	10.27	10.22	12.70
Skewness	0.90	0.50	1.42	-0.13	0.36
Min.	-36.58	-47.00	-28.25	-62.56	-59.51
Max.	68.88	72.44	90.23	39.90	61.61
VaR 99%	-21.06	-24.00	-20.97	-23.74	-31.19
VaR 95%	-12.39	-13.74	-14.52	-15.08	-18.19
VaR 90%	-8.63	-9.76	-10.85	-11.52	-13.11

Figures 1-5: Graph of Operational Risk Returns by Market
(y-axis: frequency, x-axis: operational risk returns (%))

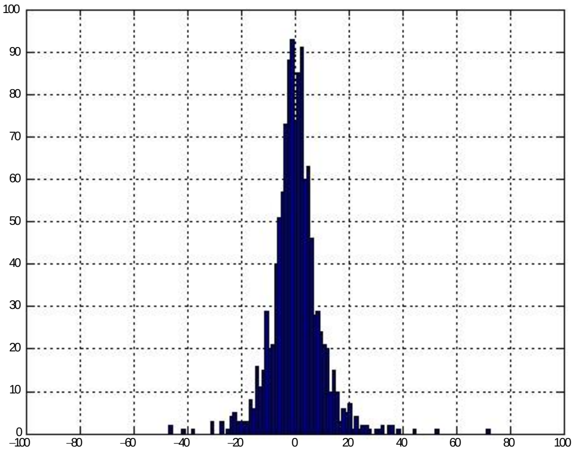

Figure 1: UK

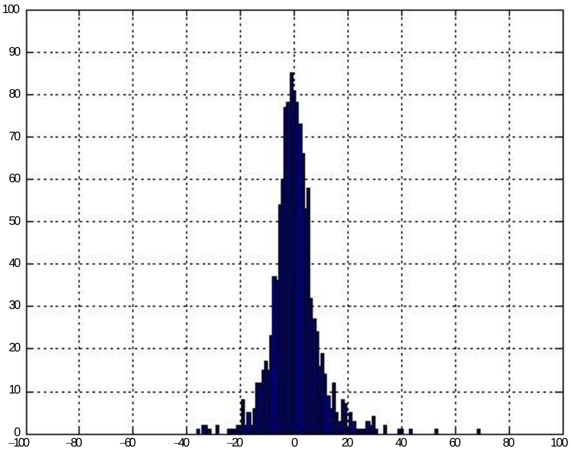

Figure 2: USA

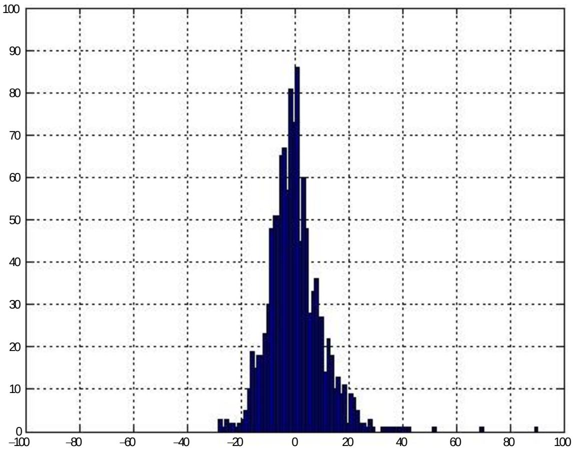

Figure 3: South Korea

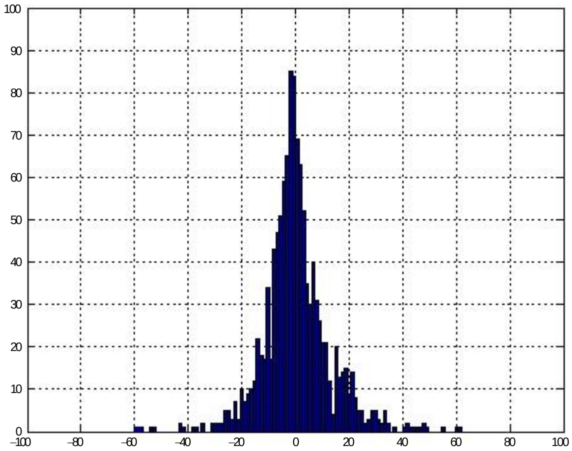

Figure 4: China

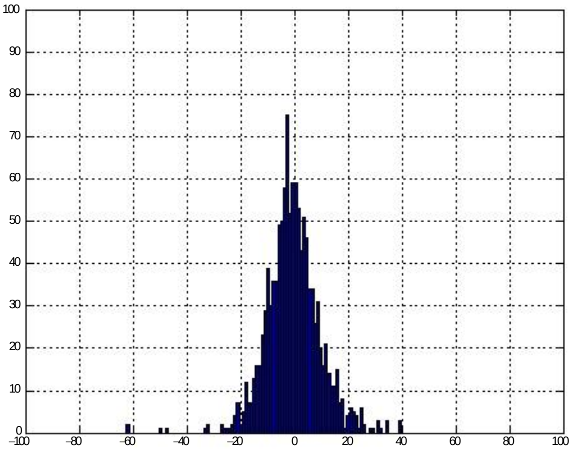

Figure 5: India

6.1.2 Operational Risk and Operational Risk Returns by Sector

Table 2: Operational Risk and Operational Risk Returns by Sector

Sector	Utilities	Technology	Basic Materials	Financial
Mean	-0.06	0.07	1.02	-0.71
S.D.	8.16	11.07	12.22	9.49
Skewness	0.52	0.15	0.77	0.56
Min.	-35.18	-62.46	-59.51	-62.56
Max.	39.93	69.93	90.23	72.44
VaR 99%	-21.80	-25.94	-29.56	-23.67
VaR 95%	-13.26	-15.63	-16.14	-14.71
VaR 90%	-8.86	-11.93	-11.57	-10.28

Figures 6-9: Graph of Operational Risk Returns by Sector
(y-axis: frequency, x-axis: operational risk returns (%))

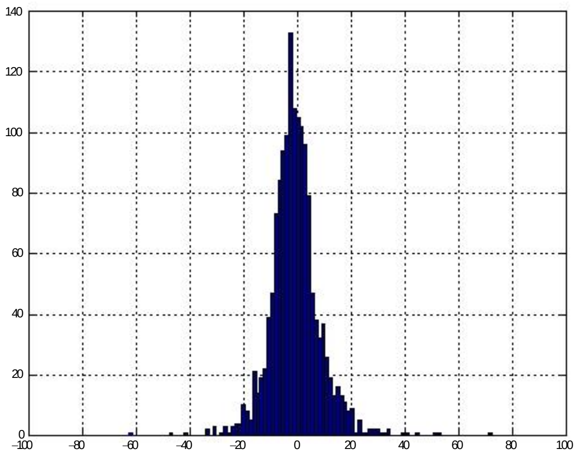

Figure 6: Financial Sector

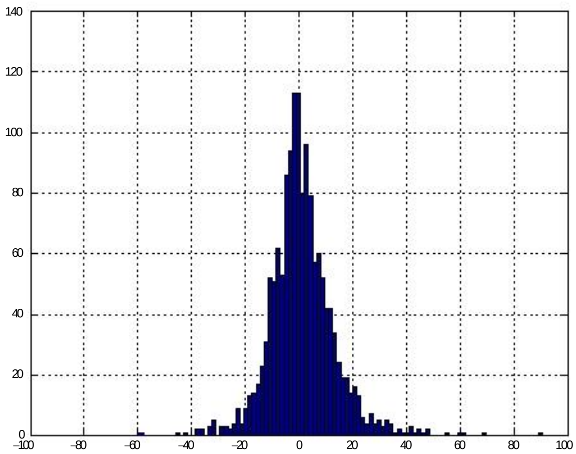

Figure 7: Basic Materials Sector

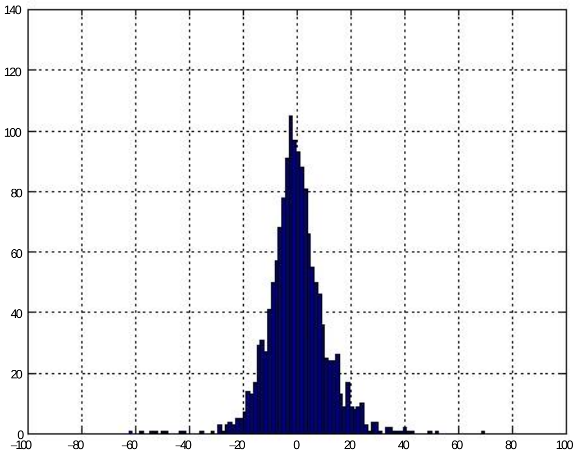

Figure 8: Technology Sector

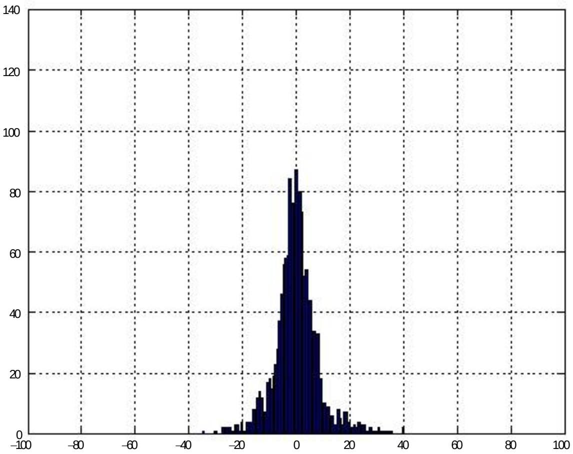

Figure 9: Utilities Sector

6.1.3 Operational Risk and Operational Risk Returns by Market and Sector

Table 3: Technology Sector for each Market

Country	China	India	S.Korea	UK	USA
Mean	-0.17	-1.07	0.45	0.77	0.36
S.D.	15.07	11.10	12.25	8.50	6.30
Skewness	-0.08	-0.62	1.21	-0.04	0.53
Min.	-57.58	-62.46	-28.25	-31.04	-20.09
Max.	49.50	39.59	69.93	24.92	25.76
VaR 99%	-43.27	-28.85	-23.85	-18.91	-13.83
VaR 95%	-22.10	-17.10	-15.65	-13.00	-7.94
VaR 90%	-16.15	-12.40	-12.90	-9.84	-6.01

Table 4: Financial Sector for each Market

Country	China	India	S.Korea	UK	USA
Mean	-0.98	0.05	-0.94	-0.99	-0.71
S.D.	7.72	9.36	8.74	10.99	10.31
Skewness	0.02	-0.78	0.47	1.09	1.16
Min.	-30.28	-62.56	-27.52	-47.00	-33.64
Max.	26.37	33.89	33.07	72.44	52.29
VaR 99%	-23.96	-22.49	-18.81	-30.46	-21.08
VaR 95%	-13.17	-13.38	-15.37	-15.85	-13.59
VaR 90%	-8.54	-9.71	-10.15	-11.89	-10.44

Table 5: Basic Materials Sector for each Market

Country	China	India	S.Korea	UK	USA
Mean	1.78	-0.79	1.63	1.62	0.86
S.D.	15.51	10.49	11.25	10.97	12.10
Skewness	0.61	0.18	2.04	0.23	0.61
Min.	-59.51	-33.81	-25.52	-45.85	-36.58
Max.	61.61	39.90	90.23	38.37	68.88
VaR 99%	-37.05	-26.72	-20.88	-24.47	-31.92
VaR 95%	-19.66	-16.39	-13.13	-14.04	-16.81
VaR 90%	-12.40	-12.53	-10.21	-9.73	-12.27

Table 6: Utilities Sector for each Market

Country	China	India	S.Korea	UK	USA
Mean	0.54	-0.26	-0.51	-0.23	0.10
S.D.	10.74	9.85	8.10	5.98	4.35
Skewness	0.26	0.82	0.81	-0.60	-0.34
Min.	-35.18	-24.78	-26.31	-27.35	-14.33
Max.	33.55	39.87	39.93	20.16	11.95
VaR 99%	-26.01	-20.88	-17.72	-17.99	-12.27
VaR 95%	-15.81	-14.33	-13.04	-9.39	-7.11
VaR 90%	-12.45	-10.75	-8.87	-6.50	-5.32

6.2 Discussion and Analysis

6.2.1 Market Effect

The results for table 1 are presented in the previous section. From table 1 it is observed that the mean operational risk returns range from -0.51 to 0.29%. Although South Korea and China achieve higher returns than the USA there is no significant difference in returns in magnitude in most of the countries; USA, UK, S.Korea and China have expected returns within a similar range. An exception is India whose expected return is significantly lower than the other 4. This implies that generally returns from operational risk are not affected by market development. It is also interesting to note that India's result appears to reflect that India is operationally less well managed (as mentioned previously).

In table 1 there is a marked difference in operational risk between the developed and emerging markets: at practically all VaR levels and standard deviation, emerging markets have higher risk levels than the developed markets. The differences are also substantial, for instance, the 90% VaR in China is -13.11% whereas in the USA it is -8.63% -China has 52% more VaR than the USA. These results are therefore consistent with the view that emerging markets have higher operational risk than in developed markets. These results are also consistent with a lack of investment in decision support systems (which would mitigate operational risk).

For the benefit of clarification, it should be noted that operational risk can arise from a number of sources. Hence it is not claimed that under investment in decision support systems is the sole cause of higher operational risk. As discussed in section 2, it is acknowledged that there is under investment in decision support systems in emerging markets and that decision support systems can directly mitigate operational risk. Since operational risk is higher in emerging markets and that decision support systems directly affect operational risk, in this context we therefore suggest that higher operational risk is consistent with lower decision support systems investment.

If one takes the operational risk equivalent of the 'Sharpe ratio' (expected return to standard deviation ratio of operational risk returns, adjusted for the riskless rate), one finds that the developed markets have higher ratios: USA (0.017), UK (0.03), South Korea (0.016), China (0.023) and India (-0.1). This suggests that developed markets are better at managing their operational risk compared to emerging markets, as one would expect, since they are taking 'better' risks. Again, this is consistent with the level of investment one would expect in decision support systems in developed markets compared to those in emerging markets. It is worth noting that China's ratio is in fact comparable to the developed markets, suggesting that the

Chinese market is better at taking risks for an emerging market, despite taking larger risks than other emerging markets.

The skewness tends to vary significantly depending on the market, for instance USA almost has 3 times the skewness of China. Overall, the developed markets tends to be higher compared to the emerging markets, with USA (0.9%) and UK (0.5%) higher than India (-0.13%) and China (0.36%). This has 2 implications, firstly a more positive skewness means the distribution is shifted to the right of the distribution. This implies that there are fewer losses associated with operational risk and this would be consistent with higher investment in decision support systems to reduce operational risk. Secondly, the significant difference in skewness across markets may account for emerging markets underestimating operational risk; skewness has been associated with underestimation of risk (hence the issue of skewness risk). Hence the difference in skewness may account for emerging markets underestimating their level of operational risk exposure.

An increasingly important area of risk management has been concerned with worst case scenarios, extreme events or tail risks. One notices in table 1 that there is difference in extreme values for emerging markets compared to developed markets but also the difference is substantial. The USA and UK have 36.58% and -47% respectively whereas China and India have -62.56% and -59.51% respectively; this is a potential difference of up to a 70% increase in extreme losses. Hence the differences in (extreme) operational risk are substantial for emerging and developed markets. Again, these can be attributed to a lack of operational risk management, which would be expected for under investment in decision support systems.

It is interest to note that for most of the risk measurement values (VaR and S.D.) and other risk values that South Korea's values are commonly in between the developed and the emerging market values. This is a reassuring result as South Korea is considered an intermediate market between developed and emerging markets and so one should expect its operational risk results to be in between the two markets. Hence this result substantiates the reliability of our operational risk measure.

6.2.2 Sector Effect

From table 2 one can observe trends in operational risk and operational risk returns according to sectors. Although there is no significant variation in operational risk returns, one notices that there is a greater variation across sectors than across markets. The financials have the lowest expected return from operational risk (-0.71%) and basic materials the highest

(1.02%) with each sector approximately distributed evenly between these 2 bounds. The developed and emerging markets mostly had expected returns within the range of 0.15-0.29%. In terms of operational risk measurement, the risk in all sectors (at different VaR levels and SD) are comparable to those in the different markets e.g. for the sectors 90% VaR ranges from -8.86% to 11.93% whereas for the markets it ranges from -8.63% to -13.11%. Hence the magnitude of operational risk variation is not dependent on sector or market.

From table 2 one notices that operational risk varies by sector. The basic materials sector is generally the most riskiest in terms of VaR and standard deviation, with utilities the least riskiest. One would expect some sectors to be operationally less risk for a number of reasons. For instance, one would expect utilities to be operationally less risky as they are highly regulated to prevent large scale operational risks, which could affect health and safety issues of the general public. On the other hand one would expect the basic materials sector to encounter higher operational risk due to the nature of the business, involving operations that are intrinsically risky. It is also observed that the variation in operational risk across sectors is comparable to the variation in operational risk from developed and emerging markets. The 99% VaR is -29.56% for basic materials while -21.8% for utilities (a difference of 36%); the S.D. is also 12.22% for basic materials whereas 8.16% for utilities (a difference of approximately 50%). Consequently, the spread in operational risk values across markets or sectors is not dependent on either.

An analysis of 'Sharpe ratios' (or the expected return to standard deviation ratio adjusted for the riskless rate) give the following results: utilities (-0.007), technology (0.006), basic materials (0.083) and financial (-0.074), hence the financial sector is the lowest with the basic materials sector as the highest. It is also observed that there is no significant variation in the ratios in terms of magnitude, in fact the range of variation is lower than compared to the range between different markets. Hence the sectors do not have a significant influence on the 'Sharpe ratios' compared to the level of market development.

Furthermore, although the basic materials sector is generally the riskiest sector, it is also able to achieve better returns from operational risks, that is this sector is better at taking good risks compared to other sectors. Although the financial sector is not the lowest or highest operational risk sector, its low Sharpe ratio implies that it is least effective at taking good risks. This is an interesting result, given that it reflects the view that the financial sector did not sufficiently manage its operational risk, which caused significant losses in the global financial crisis. This result is also reassuring as it is giving results consistent with expectations (similar to South Korea in the previous section).

The skewness does not vary significantly between sectors, with the majority in between 0.52-0.77% except the technology sector, which has 0.15%. This is in contrast to skewness variation between developed and emerging markets which varies between -0.13 to 1.42%. Consequently, sector type does not significantly impact skewness risk, unlike market development, hence underestimation of operational risk would be dependent upon market rather than sector. This result is again consistent with expectation since there is under investment in emerging markets, rather than sector based under investment.

The range of minimum and maximum values for different sectors are similar to those for different markets. The minimum values range from -35.18 to-62.56% (in the markets it is -36.58 to -62.56%) and the maximum values range from 39.93 to 90.23% (in the markets we have 39.90 to 90.23%), hence neither market nor sector has any dominant effect on the variation in tail risk. However, there are some sectors with higher extreme losses compared to others (with financial having the highest (-62.56%) and utilities the lowest (-36.58%)). This is not an unexpected result given that some sectors have operations that are fundamentally exposed to higher tail risk.

6.2.3 Sector and Market Effect

To examine how market development and sector factors jointly impact operational risk the operational risk in each sector is examined in terms of each market; see tables 3-6. In tables 3-6 the expected returns do not vary significantly for all markets and sectors. The mean returns vary from -1.07% to 1.78%, there is no discernable trend between emerging and developed markets or sectors. This is an interesting result because mean returns are fairly constant yet one may hypothetically expect mean returns to vary with sector or market, given that operational risk can be influenced by both. However, from the previous sections it was observed that mean returns do not vary with sector or market and so this result is not unexpected.

From tables 3-6 it is observed that at all risk measures the operational risk is consistently higher in emerging markets than in developed markets, regardless of sector (the only sector exception is the financial sector). For example, for the utilities the 99% VaR in India and China are -20.88% and -26.01% , respectively, whereas in UK and USA it is -17.99% and -12.27%, respectively. Furthermore, South Korea, the intermediate market, also has operational risk levels in between emerging and developed markets; for example the 99% VaR in utilities is -17.72%. Therefore the results suggests that market development directly impacts the level of operational risk and is more dominant than the sector affecting operational risk. If the sector were the more dominant factor, and given that it has already been observed that operational risk varies with each sector for each market, then it would have been expected that the operational risk varies with a particular sector rather than market development.

From tables 3-6 it is observed that the riskiest sector differs for each market. For instance at practically all risk measures for China, the technology sector is riskiest and the financial sector is the least riskiest. In the USA the basic materials sector is the riskiest and utilities sector is the least riskiest. The tail risk (specifically the minimum) and maximum values vary across sector and market development, as one would expect from our observations in previous sections. The emerging markets typically have more negative minimums than the developed markets, for instance in the basic materials sector there is China with -59.51% and USA with -36.58%. Hence both sector and market influence operational risk.

The skewness is generally higher in developed markets compared to emerging markets, for all sectors except the utilities sector. For example, in the technology sector the skewness of India is -0.62% whereas in the USA it is 0.53%. The positive skewness implies that the operational risk return distribution is shifted to the right more in developed markets compared to emerging markets, regardless of sector. This is consistent with previous results on skewness dependence on market development. Moreover skewness has been associated with underestimation of risk; these results would therefore account for emerging markets underestimating operational risk, in any sector, unlike in the developed market.

One notices that the financial sector is riskier in the developed markets compared to the emerging markets for most of the risk measures. This is an interesting result for a number of reasons. Firstly, it shows that operational risk is not always higher in emerging markets and therefore it is possible for emerging markets to outperform operational risk management of developed markets. Secondly, the results are consistent with literature that the operational risk in developed markets was higher than in emerging markets for the financial sector, causing significant losses in developed markets (e.g. model risk of financial products).

7 Conclusion

In this paper a method of measuring operational risk is provided that is not prohibited from investigating emerging markets. This also allows us to compare and benchmark the operational risk performance of emerging market firms to developed market firms, across a range of sectors. Furthermore, our operational risk results are consistent with expectations across most markets and sectors and so provides credible results. Our results and method can be continued to be explored to add to the literature and analysis on emerging markets, which is currently lacking in operational risk and decision support systems areas.

In this paper it is shown that operational risks are dependent on the level of market development (specifically emerging or developed). It is also found that operational risk is dependent on industry sector (which is expected since operational risk is fundamentally linked to business operations) but its impact is less important than market development. Consequently our results are consistent with emerging markets suffering from under investment in decision support systems. Although it is recognised that operational risk can arise from a range of sources, given that it is acknowledged that there is lower decision support systems investment in emerging markets and that such systems directly impact operational risk, in this context it suggests that higher operational risk can be attributed to under funding of decision support systems. Our results therefore support the case of increased investment in decision support systems in emerging markets.

It is found that market and sector factors affect the shape of the operational risk distribution, in particular skewness and tail risk. Also, it is found that skewness was more negative in emerging markets than in developed markets. Since skewness (risk) has been attributed to accounting for underestimation of risk, this result is consistent with emerging markets misunderstanding their operational risk exposure and so causing lower decision support systems investment. Additionally good operational risk management would also aim to reduce extreme losses, thereby reducing tail risk, and this would also be achieved from decision support systems investment. Hence the operational risk results obtained are consistent with what one would expect from emerging markets and support a lack of investment in decision support systems.

Our study will be of particular value to industry, where the impact of operational risks can significantly influence investment in emerging markets. In particular, our paper shows that there exist significant differences between emerging markets and developed markets, which is consistent with management literature on operational risk. Furthermore, our paper shows that operational risk is higher in emerging markets than in developed markets, regardless of sector, and so investment in decision support systems should aim to reduce operational risk.

8 Appendix

Table 7: Credit Risk Returns by Market

Country	USA	UK	S.Korea	India	China
Return (%)	2.64	3.03	3.52	7.36	6.67

Table 8: Riskless Returns by Market

Country	USA	UK	S.Korea	India	China
Return (%)	1.55	2.30	3.33	6.73	6.18

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